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MULTI-OBJECTIVE OPTIMIZATION OF PMEDM PROCESS PARAMETERS FOR PROCESSING CYLINDRICAL SHAPED PARTS USING TAGUCHI METHOD AND GREY RELATIONAL ANALYSIS

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ABSTRACT

This paper introduces a study on multi-objective optimization of powder mixed electric discharge machining (PMEDM) process parameters for processing cylindrically shaped parts. In the study, five parameters, including the pulse current, the server voltage, the pulse on time, the pulse off time, and the powder concentration, were selected for the investigation. Besides, the surface roughness and the electrode wear were chosen as two objectives for the optimization problem. In addition, the Taguchi method and the grey relational analysis were combined to optimize both the surface roughness and the wear of the electrode simultaneously to find the optimum input parameters. The effect of the input parameters on the overall goal was assessed. Moreover, optimum PMEDM process parameters for multi-objective was proposed. A comparison of calculated and test results shows high accuracy and efficiency.

KEYWORDS: PMEDM, Silicon Carbide Powder, Multi-Objective, Cylindrical Shaped Part, Taguchi Method & GRA

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Original Article

1. INTRODUCTION

Electrical discharge machining (EDM) is a type of non-traditional machining methods which can be used to machine any conductive materials [1]. It is the most common machining method for processing materials featuring electro-conductivity, high-hardness [2]. It has various advantages such as - it can process cavities with thin walls, parts with difficult geometry, or it can process with burr-free [3]. Therefore, EDM is used widely to process various types of conductive materials such as Al2O3 ceramic [4], γ-TiAl intermetallic alloys [5, 6], Inconel 718 [7-9], Ti6Al4V [10-12], SKD11 [13-15], etc. Also, it was reported that EDM is the most commonly used for machining dies and molds [16]. Recently, several authors [17, 18] have reported that EDM can be used effectively to process cylindrically shaped parts such as tablet punches.

Although it has many advantages, the EDM process has some restrictions such as high cost of EDM system, low productivity, and fast electrode wear. Therefore, many efforts have been made to improve the effectiveness of the EDM process such as to increase the material removal rate (MRR) [19-21], the quality of EDM surfaces [19, 22, 23], or to reduce the wear of the electrodes [19, 24, 25].

An effective method to improve the efficiency of the EDM process is to add metal powders to the dielectric solution. This method is called powder mixed electrical discharge machining (PMEDM). Adding metal powders into the dielectric fluid can make the process becomes more stable, thereby, improving the Material Removal Rate (MRR) and surface quality [26]. It was noted that PMEDM could increase the MMR up to 54%

when processing γ-TiAl intermetallic [23] or up to 48.43% when machining aluminum alloy 6061/10% SiC composite [27] and reduce the surface roughness to 32% compared to EDM [23]. Moreover, it can increase the microhardness of the machining surface [28] and reduce the wear of the electrodes [29]. For these reasons, many studies have focused on PMEDM to improve the efficiency of this process. In particular, the Taguchi method and the gGey Relational Analysis (GRA) are used in many studies [30, 31] to optimize many different objectives simultaneously.

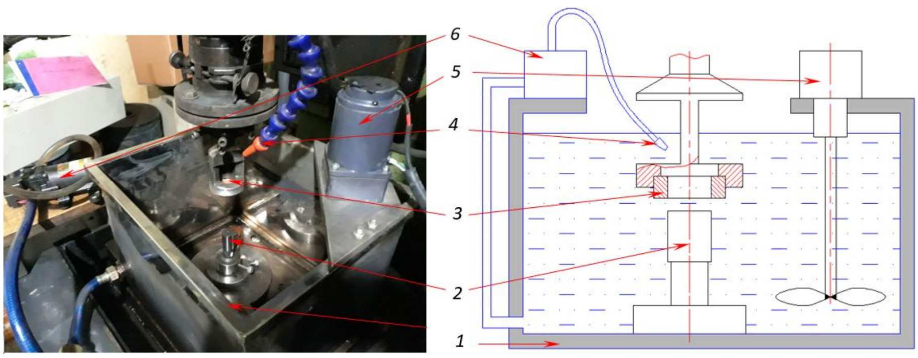
In this study, the combination of the Taguchi method and GRA was applied to optimize the problems related to the surface roughness and the electrode wear in the PMEDM process when processing cylindrically shaped parts. The effect of the input process parameters on the multi-objective response was investigated through a grey relational grade. In addition, optimum input parameters for multi-objective were proposed.

2. EXPERIMENTAL WORK

In this work, an experimental setup for the PMEDM process was conducted (Figure 1). In the setup, a CNC machine (AG40L - Sodick Europe Ltd. UK) is used as a die-sinking EDM system. Also, 90CrSi alloy tool steel and copper were selected as the workpiece and the electrode materials and HD-1 oil as the dielectric medium. In addition, 45-55 (nm) silicon carbide powders are chosen to add to the dielectric fluid.

Table 1: Input Parameters and their Levels

Paramerters	Symbol	Levels		
		1	2	3
Pulse ontime (μs)	T_{on}	6	14	-
Powder concentration (g/l)	C_p	0	0,03	0,06
Pulse off time (μs)	T_{off}	14	21	30
Pulse current (A)	IP	4	8	12
Server voltage (V)	SV	3	4	5



1) Machining tank; 2) workpiece; 3) electrode; 4) stirring; 5) magnets

Figure 1: Experimental Setup.

Table 1 shows five factors and their levels are considered in this work. The factors include the pulse on time, the pulse off time, the pulse current, the server voltage, and the powder concentration. Besides, the Minitab 19 software and the Taguchi method are used to design and plan experiments. Experiments are conducted with four factors at three levels, and one factor at two levels and hence mix orthogonal array (L18 (3^4 and 2^1)) is chosen. Table 2 describes the experimental plan and response values.

Table 2: L18 (34 and 21) Orthogonal Array with Factors and Responses

TT	*Ton*	*Cp*	*Toff*	*IP*	*SV*	*Ra (µm)*		*EW (g)*	
						TB	*S/N*	*TB*	*S/N*
1	6	0	14	4	3	3.075	-9.758	0.103	19.743
2	6	0	21	8	4	2.330	-7.348	0.132	17.611
3	6	0	30	12	5	3.124	-9.894	0.082	21.724
4	6	0.03	14	4	4	3.177	-10.040	0.108	19.332
5	6	0.03	21	8	5	2.434	-7.725	0.125	18.039
6	6	0.03	30	12	3	3.211	-10.132	0.094	20.568
…									
17	14	0.06	21	4	5	5.273	-14.441	0.004	47.264
18	14	0.06	30	8	3	7.027	-16.936	0.012	38.416

3. RESULTS AND DISCUSSIONS

After having experimental data (Table 2), Taguchi method and GRA are applied to solve the multi-objective optimization problem in which the Ra and EW are minimized simultaneously. In practice, the steps in multi-objective optimization using Taguchi method and GRA have received a lot of attention [32-37]. In this study, only basic calculation steps are presented:

Step 1 Calculating S/N Ratio for the Corresponding Responses

The goal of this study is to determine the optimum input factors to achieve two goals simultaneously: "smaller - the - better" for both the surface roughness and the electrode wear. Therefore, the S / N ratio is determined by the following formula:

$$S/N = -10log_{10}\left(\frac{1}{n}\sum_{i=1}^{n} y_i^2\right) \quad (1)$$

In which, n is the number of experimental repeated times; in this work n=3; yi is measured value the ith measurement with i = 1, 2…n. The calculated results of the S / N ratio of both objectives are shown in Table 2.

Step 2 Normalizing S/N Values

The higher S/N ratio will lead to a maximum confident level and less noise result. Also, the S/Nij is normalized by Zij (0≤Zij≤1) which is determined by the following equation to avoid the effect of adopting different units and to reduce the variability:

$$Z_{ij} = \frac{S/N_{ij} - \min\left(S/N_{ij}, j=1,2,\ldots k\right)}{\max\left(S/N_{ij}, j=1,2,\ldots k\right) - \min\left(S/N_{ij}, j=1,2,\ldots k\right)} \quad (2)$$

Wherein, j = 1, 2…k (k is the number of experiments). The calculated values of Zij and Δj(k) are given in Table 3.

Table 3: Zij Values and Absolute Value □j(k)

Trial No.	Zij		$\Delta_j(\kappa)$	
	Ra	EW	Ra	EW
	Z_0(k)			
	1.00	1.00		
1	0.744	0.257	0.256	0.743
2	0.979	0.200	0.021	0.800
3	0.731	0.311	0.269	0.689
4	0.717	0.246	0.283	0.754
5	0.942	0.211	0.058	0.789

6	0.708	0.279	0.292	0.721
…				
17	0.288	1.000	0.712	0.000
18	0.045	0.761	0.955	0.239

Step 3 Calculating the Grey Relational Co-Efficient for the Normalized S/N Values

$$\gamma_j(k) = \frac{\Delta min + \zeta\Delta}{\Delta_j(k) + \zeta\Delta} \tag{3}$$

In which, ζ is distinguishing coefficient which depends on the requirements of actual system: 0≤ζ≤1; in this work ζ =0.5. Δj(k) is the deviation sequence:

$$\Delta_j(k) = \left\| Z_0(k) - Z_j(k) \right\| \tag{4}$$

$$\Delta min = min_{\forall j \in i}\, min_{\forall k} \left\| Z_0(k) - Z_j(k) \right\| \tag{5}$$

$$\Delta max = max_{\forall j \in i}\, max_{\forall k} \left\| Z_0(k) - Z_j(k) \right\| \tag{6}$$

Step 4 Generating the Grey Relational Grade

Figure 2 and Table 4 show the grey relational grades which are calculated by the following equation:

$$\bar{\gamma}_j = \frac{1}{k}\sum_{i=1}^{m} \gamma_{ij} \tag{7}$$

where, is the grey relational grade for the j[th] experiment; k is the number of objectives (k=2) (Ra and EW).

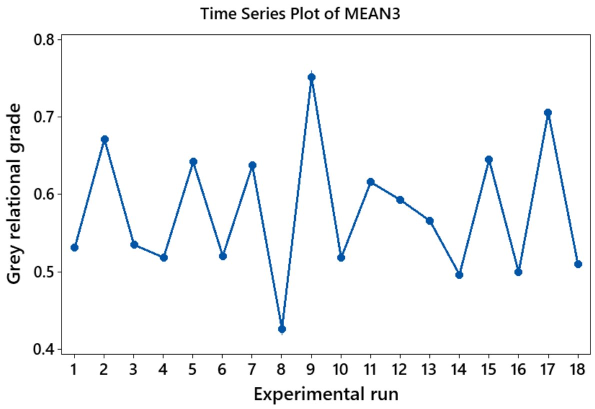


Figure 2: Grey Relational Grade for Ra_{min} and EW_{min}

Table 4: Grey Relational Co-Efficient and Grey Grade Values

TT	Grey Relational co-Efficient γ_i		$\bar{\gamma}$
	Ra	EW	
1	0.661	0.402	0.532
2	0.959	0.384	0.672
3	0.650	0.420	0.535

4	0.638	0.399	0.518
5	0.896	0.388	0.642
6	0.631	0.410	0.520
…			
17	0.412	1.000	0.706
18	0.344	0.677	0.510

Table 5: Main Effects on Grey Relation Grades

Level	Ton	Cp	Toff	IP	SV
1	0.5816	0.5775	0.5452	0.6281	0.5521
2	0.5723	0.5647	0.5931	0.6034	0.5590
3		0.5886	0.5926	0.4993	0.6198
Delta	0.0093	0.0238	0.0479	0.1288	0.0677
Rank	5	4	3	1	2

Step 5 Determining the Optimum Parameters and their Level Combinations

Theoretically, a higher gray relation grade implies better product quality. Therefore, based on the grey relational grade, it is possible to estimate the impact of the factors, and the optimum level for each factor can be controlled. From Table 4 and Figure 2, the 9th experiment (T_{on}2/C_p3/T_{off}3/ IP1/SV3or T_{on}= 14 (µs), Cp = 0.06 (g/l), T_{off} = 30 (µs), IP = 12 (A), SV = 5 (V)) has the maximum grey relational grade (0.754). However, they are not optimum factors. To find the optimum input factors, the Taguchi method is used to determine the relation among the input factors and the grey relation grades. The analyzed results are shown in table 5 and figure 3.

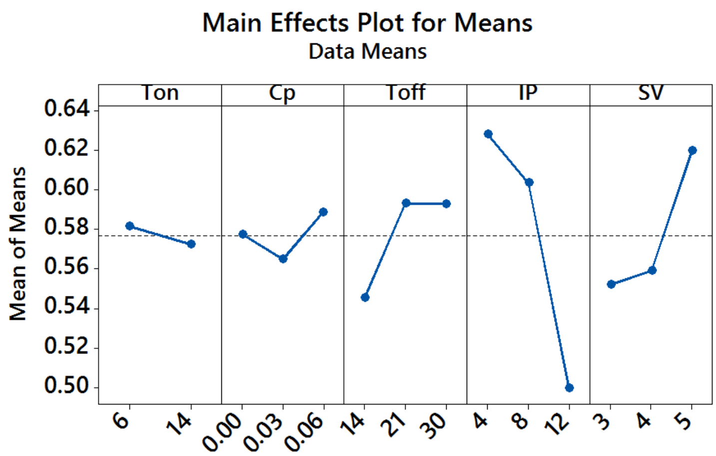


Figure 3: Main Effects Plot for Means.

Table 6: Results of ANOVA on Grey Grade

Source	DF	Seq SS	Adj SS	Adj MS	F	P	C%
Ton	1	0.000392	0.000392	0.000392	0.08	0.787	0.32
Cp	2	0.001707	0.001707	0.000853	0.17	0.846	1.38
Toff	2	0.009089	0.009089	0.004545	0.91	0.441	7.33
IP	2	0.056037	0.056037	0.028018	5.60	0.030	45.22
SV	2	0.016634	0.016634	0.008317	1.66	0.249	13.42
Residual Error	8	0.040058	0.040058	0.005007			32.33
Total	17	0.123917					100.00

It can be seen from table 5 and table 6 that the discharge current IP has the strongest effect on the common goal (Ramin and EWmin), followed by the servo voltage SV, the pulse off time T_{off}, the nano powder concentration C_p and the pulse on time T_{on} has the lowest effect.

The maximum grey coefficient of each factor indicates the optimum level of that factor. Therefore, according to Table 5 and Figure 3, the set of optimum input factors for both the surface roughness and the electrode wear are: (T_{on}1/C_p3/T_{off}2/ IP1/SV3or T_{on}= 6 (µs), Cp = 0.06 (g/l), T_{off} = 21 (µs), IP = 4 (A), SV = 5 (V).

Step 6 Determining Predict Model

The optimum grey relation grade is determined as:

$$\overline{\mu_{op}} = \overline{A_1} + \overline{B_3} + \overline{C_2} + \overline{D_1} + \overline{E_3} - 4 * \eta_m \tag{8}$$

where, η_m is the average of grey relation grades (η_m = 0.577); , $\overline{B_3}, \overline{C_2}, \overline{D_1}$, and are the maximum grey relation grades corresponding to each input parameter.

From Table 5, $\overline{A_1} = \overline{1}$ = 0.5816; $\overline{B_3}$ = = 0.5886; $\overline{C_2} = \overline{1}$ = 0.5931; $\overline{D_1}$ = = 0.6281; $\overline{E_3}$ = = 0.6198. Substituting these values into Equation (8), the optimum grey relation grade is equal to 0.703.

Similarly, applying the above equation for the optimum factors, the predict model of the SR and EW can be determined as:

$$(Ra, \mathrm{EW})_{op} = \overline{T_{on1}} + \overline{C_{p3}} + \overline{T_{off2}} + \overline{IP_1} + \overline{SV_3} - 4 * \overline{T} \tag{9}$$

In which, $\overline{1}$ is mean value of Ra or EW corresponding to T_{on} at level 1 (6 µs); is the mean value of Ra or EW corresponding to C_p at level 3 (0.06 g/l); $\overline{T_c}$ is mean value of Ra or EW corresponding to T_{off} at level 2 (21 µs); is the mean value of Ra or EW corresponding to IP at level 1 (4 A); is the mean value of Ra or EW corresponding to SV at level 3 (5 V); is the mean value of SR or EW of the total experiments. Therefore, the optimal values of Ra and EW are found as:

$$(Ra)_{Toiuu} = 2{,}896 + 4{,}673 + 4{,}451 + 4{,}193 + 4{,}142 - 4 * 4{,}401 = 2{,}749\ (\mu m) \tag{10}$$

$$(EW)_{op} = 0{,}11889 + 0{,}076 + 0{,}09833 + 0{,}04383 + 0{,}04522 - 4 * 0{,}06459 = 0{,}1239\ (g) \tag{11}$$

Step 7 Evaluating Predict Model

To evaluate the predict model, an experiment have been carried out with the optimum input factors (T_{on}= 6 (µs), Cp=0.06 (g/l); T_{off} = 21 (µs), IP = 4 (A), SV = 5 (V). The experiment was repeated two times, and its results are given in Table 7, along with the calculation results from the proposed model. From the results, it is reported that the error between the two methods is small (only 6.77 %), and it can be used in practice.

Table 7: Calculated and Experimental Results

Objective Properties	Optimum Process Parameters		
	Calculation	Experiment	% difference
	$T_{on1}/C_{p3}/T_{off2}/IP_1/SV_3$	$T_{on1}/C_{p3}/T_{off2}/IP_1/SV_3$	
Surface roughness (µm)	2.749	2.563	6.77
Electrode wear (g)	0.1239	0.1189	4.04
Grey relational grade	0.703		

4. CONCLUSIONS

The present study aims to optimize the input factors when PMEDM cylindrical shaped parts with silicon carbide power to minimize the surface roughness and the electrode wear by using the Taguchi method and the grey relational analysis. In the study, eighteen experiments, including the pulse on time, the pulse off time, the pulse current, the server voltage, and the powder concentration, are planed based on an orthogonal array L18 (3^4 and 2^1). From the results of the study, it is found that the discharge current has the strongest influence on the common goal (Ramin and EWmin), followed by the servo voltage, the pulse off time, the nano powder concentration, and the pulse on time. In addition, to minimize the surface roughness and the electrode wear, the optimum input factors are T_{on}= 6 (µs), Cp=0.06 (g/l); T_{off} = 21 (µs), IP = 4 (A), and SV = 5 (V). Also, the predicted model has been verified experimentally, and this model can be applied for use in practice.

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